Content- and Relation-Integrated Interdisciplinary User Recommendation Model for Academic Social Media: A Postprint

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Date: 2023-04-01T16:15:53+00:00

Abstract

[Purpose/Significance] In the era of rapid development of academic social media, many scientific collaborations originate from acquaintances or follows on social media when conducting interdisciplinary research or seeking interdisciplinary collaboration. Therefore, implementing interdisciplinary user recommendation on social media is of great significance. Social media primarily contains two major categories of data: "media" (representing content) and "social" (representing relationships). Accordingly, this paper investigates interdisciplinary user recommendation on social media that integrates content and relationships.

[Method/Process] Following user representation based on the vector space model, this study calculates user domain expertise by leveraging user content information, measures user interdisciplinary distance based on relationship data, and simultaneously incorporates the PageRank values of the user relationship network to generate recommendation results.

[Results/Conclusion] Taking ScienceNet as an example, this research implements interdisciplinary user recommendation across five domains: "Library and Information Science," "Computer Science," "Journalism and Communication," "Higher Education," and "Biology." Through manual experimental testing and verification, the results demonstrate that the recommendations can, to a certain extent, satisfy the requirements.

Full Text

Abstract

[Purpose/Significance] With the rapid development of academic social media, many scientific research collaborations begin through acquaintances or connections on social media platforms when users engage in interdisciplinary research or seek interdisciplinary cooperation. Therefore, investigating interdisciplinary user recommendation on social media is highly meaningful. Social media primarily contains two types of data: "media" (representing content) and "social" (representing relationships). This paper proposes an interdisciplinary user recommendation approach for social media that integrates both content and relationship data. [**Method/Process**] After representing users based on the Vector Space Model, we calculate user domain specialization using content information, measure user interdisciplinary distance based on relationship data, and generate recommendation results combined with the PageRank values of user relationship networks. [**Result/Conclusion**] Using ScienceNet as a case study, we implemented interdisciplinary user recommendation across five fields: "Library and Information Science," "Computer Science," "Journalism and Media," "Higher Education," and "Biology." Manual experimental testing demonstrated that the recommendation results can meet requirements to a certain extent.

Keywords: interdisciplinary users; recommendation model; interdisciplinary distance; academic social media

Introduction

In daily life, when people encounter problems, they often hope to obtain answers from relevant domain users online. Many real-world scenarios illustrate this need [1-2]. For instance, in project review processes, domain users (or experts) are required to evaluate and assess projects, necessitating systems that recommend users based on project relevance. With the development of Internet and Web 2.0 technologies, the importance of networks in scientific research has grown increasingly significant. Platforms such as F. Barjak's ScholarMate (Research Friend), ScienceNet blogs, and Academic Circles have become popular among scholars.

As academic social media continues to develop, scholars, teams, and institutions from various fields have joined these platforms to share their achievements and communicate with peers, providing valuable support for interdisciplinary research and collaboration [7]. However, this also increases the difficulty of finding suitable interdisciplinary users (or experts) on academic social media. Therefore, conducting interdisciplinary user recommendation on academic social media is crucial and meaningful. This represents the research motivation of this paper—interdisciplinary user recommendation on academic social media. Such recommendations can satisfy users' needs to find cross-domain users in certain scenarios, helping them accurately identify relevant experts (typically, if a user has mastered a subject or has unique insights, we refer to them as an expert in that field).

Academic social media, also known as "Academic Social Networking" (ASN), refers to online services, tools, or platforms that help researchers establish social networks with other scholars and facilitate scientific research activities [6]. Currently, popular academic social media platforms abroad include ResearchGate, Academia.edu, and Mendeley, while domestic platforms include ScholarMate and ScienceNet blogs.

Unlike general information retrieval systems, recommendation systems do not directly provide answers to questions but rather offer pathways to solutions. Therefore, this recommendation model shares many similarities with existing expert recommendation systems. This paper aims to construct such an interdisciplinary user recommendation model that integrates "social" data (representing relationships) and "media" data (representing content) to achieve interdisciplinary user recommendation on academic social media.

2. Academic Social Media and Interdisciplinary Research Status

As a category of social media oriented toward academic research, academic social media content primarily originates from research users. Consequently, research on academic social media has mainly concentrated on three aspects: (1) user behavior and disciplinary differences, (2) academic impact, and (3) academic resource recommendation.

Regarding user behavior and disciplinary differences, H. Meishar-Tal et al. analyzed questionnaires from 298 users across three Israeli academic institutions based on uses and gratifications theory, finding that the primary purpose of using ASN was information consumption, while information sharing and interaction with others were relatively weak [8]. J.L. Ortega analyzed profiles of 132 Spanish National Research Council members with academic social media accounts, discovering that Academia.edu hosted a large number of humanities and social scientists, while ResearchGate was more popular among biologists [9], with observable disciplinary differences on each ASN platform. A.M. Elsayed analyzed questionnaires from 315 Arab researchers, finding that many had ResearchGate accounts, primarily from natural and applied sciences fields [10].

In terms of academic impact, J. Priem et al. argued that social networks show potential in Scientometrics 2.0, with Social Web metrics enriching traditional citation-based evaluation indicators, and that resource aggregation services could even prevent the "Sleeping Beauty" phenomenon [11]. W. Gunn considered Mendeley as one of the altmetric indicators for evaluating academic journal impact factors [12].

For academic resource recommendation, L. Jing et al. proposed the ACRRec model based on a random walk model, considering co-authorship order, latest collaboration time, and collaboration frequency to achieve collaborator recommendation [13]. V.A. Rohani et al. proposed an ECSN algorithm for cold-start problems to recommend academic projects to users [14].

With the development of academic social media, scholars have gradually recognized the role of ASN in interdisciplinary research. S.J. Oh et al. [15] analyzed 21,679 groups and 67,562 relationships on Mendeley, finding that 43,124 relationships (63.8%) occurred within users' own disciplines, while the remaining 36.2% indicated that users might have broken disciplinary boundaries by joining other disciplinary groups. Additionally, Mendeley groups demonstrate clear disciplinary diversity, providing a platform for researchers from different backgrounds to find each other and collaborate on common interests, thereby promoting multidisciplinary cooperation. J. Jiang et al. [16] constructed group-member coupling networks and group-following coupling networks on Mendeley to study interactions between groups and disciplines, noting that academic social media groups hold promise for interdisciplinary research. X. Wu et al. [17] utilized ScienceNet's disciplinary classification system, research directions filled in by research users, and friend relationship data, borrowing the phylogenetic species evenness indicator from biology to identify high-impact interdisciplinary users.

These studies demonstrate that academic social media has advantages for resource recommendation and promotes interdisciplinary research. However, research on interdisciplinary user recommendation on social media remains scarce, despite its crucial role in facilitating interdisciplinary project collaboration and scientific innovation.

Interdisciplinary user recommendation shares many similarities with traditional recommendation systems. Currently, the most studied area is expert recommendation, with a clear definition proposed by T. Reichling et al. [18]: expert recommendation is a system that helps users find relevant domain experts to solve problems in specific scenarios. Existing expert recommendation systems mainly include: (1) knowledge-based recommendation, (2) social network analysis-based recommendation, and (3) hybrid approaches.

Knowledge-based recommendation calculates the matching degree between expert knowledge and user needs after constructing expert profiles. For example, Li Ming et al. [19] introduced information entropy to solve the matching degree between requirement models and expert knowledge models. Social network analysis-based recommendation establishes expert social networks to extract expert relevance (reflected in potential exchanges such as academic issues or group communications), then mines experts through network relationships, as proposed by J.M. Kleinberg [20] with graph-based expert knowledge recommendation methods. Hybrid approaches include Xu Yunhong's [21] combination of social network analysis and semantic analysis for expert knowledge recommendation, and H. Kautz et al.'s [22] ReferralWeb.

Purely knowledge-based recommendation suffers from cold-start problems, while purely relationship-based mining lacks semantic understanding. Therefore, this paper proposes an interdisciplinary user recommendation approach that integrates content ("media" data) and relationships ("social" data) to help users more conveniently find influential interdisciplinary users that interest them.

3. Interdisciplinary User Recommendation Model Integrating Content and Relationships

Professor Peng Lan from Tsinghua University [23] identified two main characteristics of social media: first, the combination of content generation and social interaction; second, users rather than website operators are the protagonists on the platform. Therefore, this paper proposes a method that integrates content and social interaction for interdisciplinary user recommendation, with the research framework shown in Figure 1 [Figure 1: see original paper].

As shown in Figure 1, the recommendation model mainly includes three components:

(1) **User Knowledge Representation Model.** In text mining, documents are often represented using the Vector Space Model (VSM), which defines documents as vectors in a real number field, making natural language computable. In this paper, both recommendation requirements and interdisciplinary users are treated as documents, with VSM construction detailed in Section 3.1.

(2) **Recommendation Similarity Calculation.** This paper calculates similarity from two perspectives: domain direction and domain knowledge. Higher similarity values indicate better matching between recommendation requirements and user information, and vice versa. Detailed techniques are provided in Section 3.2.

(3) **Recommendation Index Calculation and Result Output.** After obtaining domain similarity values, for users exceeding a specified threshold, the recommendation ranking is generated by combining user domain specialization, interdisciplinary distance, and scholar PageRank values. Detailed techniques are provided in Section 3.3.

3.1 User Knowledge Representation Model

To calculate the distance between user information and requirement information, we adopt VSM to define the user model. The basic idea of this model assumes that the probability of word occurrence in documents is independent in terms of content and position. The Vector Space Model was proposed by G. Salton et al. in 1974 [24] and was later applied to many personalized recommendation systems such as WebWatcher and Fab, demonstrating good performance.

In this paper, we segment user blog posts, remove stop words, and construct user document vectors. Let the keyword set contained in domain knowledge be T, where $T = \{T_1, T_2, ..., T\}$, with a total of n keywords. The user set is denoted as E, where $E = \{E_1, E_2, ..., E\}$, and the user vector representation is: $E = (T_1, w_1), (T_2, w_2), ..., (T, w)$, where w represents the weight of keyword T. The weight w is calculated using TF-IDF, with the formula:

$w(T, E) = tf(T, E) \times \log((m + 1) / m)$ (1)

where tf(T , E) is the frequency of keyword T in user E 's blog posts, m is the total number of users, and m is the number of users whose posts contain keyword T .

3.2 Recommendation Similarity Calculation

The above similarity calculation can effectively retrieve domain users who meet requirements in terms of domain direction and domain knowledge. However, it may result in low recommendation precision, where users with strong interdisciplinary capabilities might be ranked lower. In project review, literature [25-26] incorporates expert research capabilities into expert selection criteria from a scientometric perspective, focusing on research direction, academic level, research experience, and reputation.

To overcome the one-sidedness of similarity calculation, this paper adopts a dual-layer similarity calculation combining requirements with domain direction and domain knowledge. The dual-layer similarity formula is defined as:

$\mathrm{Sim}(U , E) = \alpha \cdot \mathrm{Sim}(DU , E) + \beta \cdot \mathrm{Sim}(KU , E)$ (2)

where $\alpha + \beta = 1$, and $\alpha \leq \beta \leq 1$. Here, α reflects the importance of domain direction in recommendation, while β reflects the importance of domain knowledge. Sim(DU , E) represents the domain direction similarity between user requirement U and domain user E , and Sim(KU , E) represents the domain knowledge similarity between them.

When calculating similarity between users, Euclidean Distance is an intuitive and common algorithm. Smaller Euclidean distance indicates greater similarity, while larger distance indicates less similarity. In practice, similarity is typically compared to 1, with values ranging from $0 \leq \mathrm{Similarity}(X, Y) \leq 1$, where values closer to 1 indicate higher similarity. When using Euclidean distance, we can implement this concept through 1/(Distance(X, Y)). Assuming the text feature representations of user requirement i and interdisciplinary user j are v = (w $_1$, w $_2$, …, w) and v = (w $_1$, w $_2$, …, w), the similarity based on Euclidean distance is calculated as:

Distance(v , v) = √((w - w)^2) (3)

3.3 Recommendation Index Calculation and Interdisciplinary User Recommendation

The recommendation index (Recommendation Index, RI) is calculated from three perspectives: scholar domain specialization, interdisciplinary distance, and scholar network centrality. We consider the recommendation index as a weighted linear combination of domain specialization (S), interdisciplinary distance (IDD), and scholar PageRank value (PR):

$RI = \alpha_1 \cdot S + \alpha_2 \cdot IDD + \alpha_3 \cdot PR$ (4)

where: - **Domain Specialization.** Author specialization [27] was proposed by A.L. Porter et al. to describe the distribution of a researcher's publications across disciplines within a specified time. This indicator was also used in Yang Liangbin et al.'s [28] interdisciplinary measurement methods. The original formula is:

Sp = (m ^{2}) / (m)^2 (5)

where m represents the number of articles belonging to discipline category i. Lower Sp values indicate higher interdisciplinary research and lower specialization, while higher Sp values indicate more concentrated research and higher specialization.

However, He Jingfei et al. [29] found that most Sp values were below 0.5, while in reality, authors' research specialization was not that low. Therefore, we adopt He Jingfei's modified S formula:

S = 1 - (Q - 1) / (n - 1) (6)

where $Q = 1\times f_1 + 2\times f_2 + \ldots + n\times f$, and f represents the proportion of papers in each discipline category, with $f_1 \geq f_2 \geq \ldots \geq f$.

- **Interdisciplinary Distance (IDD).** IDD measures a user's interdisciplinary degree, with its concept originating from [30]. In [30], the authors noted that IDD was inspired by Phylogenetic Species Evenness from biology [31]. The formula is:

IDD = (mdiag(C)'M - M'CM) / (m^2 - $\bar{m}$m) (7)

where C is the relationship matrix of the phylogenetic tree, diag(C)' is the diagonal matrix of C, M is the column vector of species count distribution, m is the total number of species in the tree, and $\bar{m}$ is the average number of species per branch.

The IDD calculation is implemented on a phylogenetic tree. This paper innovatively constructs a user discipline phylogenetic tree based on the disciplinary distribution of users' friends. A discipline phylogenetic tree is a concept borrowed from biology. In biology, taxonomists arrange organisms on a branched tree diagram based on phylogenetic relationships to represent evolutionary history and relationships, called an "evolutionary tree." Organisms on different branches differ more than those on the same branch. Similarly, scientific disciplines have evolved and branched, with some showing clear "phylogenetic" relationships since their creation. To emphasize the "closeness" and "distance" between disciplines, this paper adopts the concept of a "discipline phylogenetic tree" to express similarity between users and disciplines.

In our experiments, the construction process of a blogger's discipline phylogenetic tree on ScienceNet is illustrated in Figure 2 [Figure 2: see original paper]. To construct the interdisciplinary relationship tree, we obtained the platform's discipline classification system by crawling ScienceNet's taxonomy: 105 secondary discipline categories (referred to as "secondary discipline categories”) grouped into 8 primary discipline categories (referred to as “primary discipline categories”), detailed in Table 1 .

Typically, users with larger interdisciplinary distances have more dispersed friend discipline distributions, while those with smaller distances have more concentrated distributions. After constructing the phylogenetic tree, we can calculate IDD values. For example, with C = $[c\ ]_{10}\times_{10}$ (where c is the shared length from species i and j to the root), M’ = [116, 95, 212, 105, 150, 98, 175, 94, 98, 77], m = 1220, and $\bar{m}$ = 122, the user’s IDD = 0.8467.

- **Scholar Relationship Network PageRank Value.** The PageRank algorithm [32], proposed by Larry Page and Sergey Brin in 1998, ranks web pages based on the principle that important pages either have many inbound links or are linked to by important pages. Therefore, a user’s PageRank value in the relationship network reflects their authority. We constructed an interdisciplinary user network (371 nodes and 7,919 edges), calculated PageRank values, and obtained sample data shown in Table 2 (Top 50).

4. Interdisciplinary User Recommendation Model Experiment and Results Analysis

4.1 Experimental Design

Based on Qiu Junping et al.’s research [33], the top 20 interdisciplinary research fields for library and information science scholars include “Computer Software and Applications,” “Journalism and Media,” “Higher Education,” etc. Corresponding to ScienceNet’s discipline classification, we selected interdisciplinary users from five fields: “Library and Information Science,” “Computer Applications,” “Journalism and Media,” “Higher Education,” and “Biology.” This included 284 interdisciplinary users identified through topic-based methods [34] and 128 identified through relationship-based methods [17], totaling 371 interdisciplinary users (with duplicates removed, the final count is less than the sum). These users had accumulated 43,598 domain blog posts, with counts detailed in Table 3 .

We merged the 43,598 blog posts by blogger ID to generate 371 interdisciplinary user documents and calculated user domain specialization S. After document creation, we 统计了博文中词的出现情况，得到 577,044 words, which after deduplication yielded 26,727 feature words. We then calculated TF-IDF weights for these features, resulting in 371 interdisciplinary user document vectors stored in the database.

Simultaneously, we extracted these users’ friend relationship networks (371 nodes and 7,919 edges), calculated PageRank values, and computed interdisciplinary distance IDD based on friends’ disciplinary distributions.

Using Visual Studio Code + Node.js architecture, we designed a recommendation model. The process is as follows: users select domain direction or domain knowledge in the recommendation model, and the system returns a Top 15 interdisciplinary user list, along with browsing links to other information (such as workplace and title). In this model, the interdisciplinary user ranking approach combines domain direction and domain knowledge similarity with weighted components (with domain specialization, interdisciplinary distance, and PageRank values all normalized before weight setting): $\alpha = \beta = 0.5$, $\alpha_1 = \alpha_2 = \alpha_3$. The recommendation model interface is shown in Figure 3 [Figure 3: see original paper].

In Figure 3, recommendations can be implemented based on requirements: (1) Users first select two different research fields from five disciplines: "Library and Information Science," "Computer Science," "Journalism and Media," "Higher Education," and "Biology." (2) Users can then select cascading "research directions," which primarily come from the secondary discipline directions filled in by the 371 interdisciplinary users. (3) After selecting "research direction," users can further select cascading "research knowledge points," which are derived from the blog post features of the 371 users. (4) Finally, clicking "Recommend" displays the results, as shown in Figure 4 [Figure 4: see original paper].

4.2 Results Analysis

To evaluate recommendation quality, we employed manual scoring. We recruited 10 doctoral and master's students from the "Library and Information Science" field and 18 from the "Computer Science" and "Communication" fields. The evaluation process was: (1) Evaluators selected their interested discipline fields, directions, and knowledge points based on their recommendation needs, then clicked "Recommend." (2) After receiving recommendations, evaluators scored each of the 10 recommended interdisciplinary users on a 1-5 scale (higher scores indicating better match with requirements).

During evaluation, we required evaluators to click each "User ID" (with hyperlink) in the "Recommendation Application" to view detailed user information. Each evaluator recorded recommendation needs and recommended users, selecting at least one set (no more than two) of recommendation needs. This yielded 35 recommendation needs and evaluation results, detailed in Table 4 .

Table 4 shows that: (1) The "(Library and Information Science, Computer Science)" combination was most frequently requested, likely because most evaluators came from these fields. (2) Discipline directions like "Information Science" and "Educational Psychology" were also frequently selected.

We further 统计了测评人员对推荐结果的评分. Across the 35 recommendation needs, we obtained 112 user ratings. The score distribution is shown in Figure 5 [Figure 5: see original paper].

Figure 5 shows that users scoring 3 and 4 account for 62% of all recommended users, with an average score of 3.14. This indicates that the recommendation model achieves a certain level of accuracy.

5. Conclusion and Future Work

To effectively integrate "media" and "social" data for interdisciplinary user recommendation on academic social media, we designed and implemented an interdisciplinary user recommendation model based on previous research. The model uses VSM to represent interdisciplinary users, employs Euclidean distance for similarity calculation, and generates recommendation lists based on a recommendation index combining domain specialization, interdisciplinary distance, and scholar PageRank values. Using interdisciplinary users from five ScienceNet fields ("Library and Information Science," "Computer Science," "Journalism and Media," "Higher Education," and "Biology") as experiments, we conducted interdisciplinary user recommendations. To evaluate quality, we invited 28 graduate students to participate in the assessment. Analysis of 35 recommendation needs from 28 testers yielded 112 recommended users with an average score of 3.15, demonstrating the model's recommendation accuracy.

This paper focused only on interdisciplinary users from five fields on ScienceNet. Future work could expand to more fields and more interdisciplinary users.

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Author Contributions

Zhang Chengzhi: Paper revision and experimental results verification design.
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Research on Interdisciplinary User Recommendation Model in Academic Social Media Combining Content and Relationships

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Abstract: [Purpose/significance] With the rapid development of academic social media, when users do interdisciplinary research or seek interdisciplinary cooperation, many scientific research cooperations start from acquaintance or attention on social media, so it is very meaningful to research on interdisciplinary user recommendation in academic social media. There are two main types of data in social media: media (represents content) and social (represents relationship). Therefore, this paper recommended interdisciplinary users integrating content and relations. [Method/process] After user modeling based on Vector Space Model, this paper calculated user specialization with user content information, measured user's interdisciplinary distance based on relational data, then gave recommendation results combined with PageRank value of user relationship network. [Result/conclusion] Taking the science blog as an example, an interdisciplinary user recommendation model in five fields of "Library and Information," "Computer," "News and Media," "Higher Education" and "Biology" has been implemented, which has been tested by artificial experiments, and showed that the recommendation results can meet the recommendation requirements to some extent.

Keywords: interdisciplinary users; recommendation model; interdisciplinary distance; academic social network

Note: Figure translations are in progress. See original paper for figures.